

Soft Computing Approach to Safe Navigation of Autonomous Planetary Rovers

Edward Tunstel, Hodayoun Seraji, Ayanna Howard

11.1 INTRODUCTION

During the past decade, NASA has been engaged in the conceptualization and implementation of space flight missions to planet Mars. As an integral part of its initiatives to explore the planet's surface, NASA has opted to employ mobile robots that are designed to rove across the surface in search of clues and evidence about the geologic and climatic history of the planet. These planetary rovers must have mobility characteristics that are sufficient for traversing rough and rugged terrain. Moreover, due to the extreme remoteness of their operating environment, Mars rovers must be capable of operating autonomously and intelligently.

The first autonomous planetary rover, named *Sojourner*, was deployed on Mars in the summer of 1997. This planetary rover was a part of the payload on the NASA Mars Pathfinder lander, which also carried a stereo imaging system, various science instruments, and a telecommunications system that served as a communications relay between Earth and the rover. *Sojourner* was used to demonstrate the viability of exploring planetary surfaces using mobile robot technology; its mission was limited to minimal scientific surface exploration confined to an area in close proximity of the lander. At NASA, the focus of ongoing research for subsequent rover deployments is on enhanced mobility and increased autonomy. In 2003, NASA plans to launch a follow-on Mars mission that will use two rovers to explore distinct regions of the planet surface. These Mars Exploration Rovers will have greater mobility and autonomy than *Sojourner* since they are expected to traverse up to 100 meters each Martian day and to conduct exploration independent of a surface lander. The longer-term technology requirements for future Mars missions call for rovers that are capable of traversing distances on the order of kilometers over high-risk and challenging terrain. This chapter describes fundamental research aimed at achieving such long-term objectives through application of soft computing techniques for safe and reliable autonomous rover navigation

11.1.1 Practical Issues in Planetary Rover Applications

Autonomous rovers designed for planetary surface exploration must be capable of point-to-point navigation in the presence of varying obstacle distributions (rocks, boulders, etc.), surface characteristics, and hazards. Mobility and navigation hazards include extreme slopes, sand/dust-covered pits, ditches, cliffs and otherwise unstable surfaces. As in the Mars Pathfinder mission scenario, the navigation task can be facilitated by knowledge of a series of waypoints (path sub-goals), furnished by mission operations personnel or an automated path planner, which lead to designated intermediate goals. Waypoints can be selected with the aid of images taken at the scene local to the rover. This mode of operation may also prevail on the 2003 rover mission, albeit with significantly longer traverse distances to locations viewable within the images captured by the rovers' on-board cameras. The round-trip communication time delay between Earth and Mars, coupled with lack of frequent opportunities for communication with landed resources on Mars makes direct control of a Mars rover all but impractical. Supervised autonomous control of the rover must therefore be achieved without the luxury of continuous or frequent remote communication between the Earth-based mission operations facility and the Mars rover.

Advanced rovers must have autonomy sufficient to avoid hazards and negotiate (if necessary) challenging terrain if they are to be of practical use for carrying out the goals of scientific exploration in an environment as harsh as the Martian surface. In essence, a capacity for safe navigation and survivability is required for the types of long-duration missions included on the NASA “Roadmap” for Mars exploration. For typical missions, rover autonomy capabilities must be provided under significant constraints on power, computation, weight, and communications bandwidth. To further increase the challenge, many popular and fast state-of-the-art processors that enable advanced capabilities in laboratory research robots are infeasible for planetary rover applications. This is due to the fact that space flight projects require the use of proven, radiation-hardened, or otherwise space flight-qualified electronics that will survive and operate in the harsh temperature and radiation extremes of space. The meager availability of fast and/or powerful space-qualified processors for on-board computation intensifies the need for efficient algorithms for implementing the necessary on-board autonomy.

In order to advance rover navigation capabilities beyond those of *Sojourner*, and even the twin Mars Exploration Rovers planned for the NASA 2003 Mars mission, advanced algorithms and computational approaches to autonomy and intelligent control must be pursued that comply with the practical constraints. Our research has revealed that the various components of soft computing hold promise as strong candidate technologies that can enable significant advances. The flexibility in applying soft computing techniques, individually or as a hybrid system, facilitates the formulation of efficient solutions to the problems of safe rover navigation in challenging terrain. We have developed a fuzzy logic-based reasoning and control framework that is complemented by neural networks and visual perception algorithms to realize a practical rover navigation system.

In the following sections, we describe the various components of the safe navigation system and several ways in which soft computing techniques have been applied to solve different aspects of the rover navigation problem. Section 11.2 provides a high level description of the navigation system and its fuzzy logic foundation. In Section 11.3, fuzzy logic methods for reasoning about rover vehicle health and safety are described. Next, a methodology for factoring perception of terrain quality into the navigation logic is presented in Section 11.4. Section 11.5 describes the fuzzy behavior-based approach and elemental motion behaviors of the system. The soft computing algorithms have been implemented on a commercial mobile robot used as a testbed for outdoor navigation research. In Section 11.6, we discuss experimental investigations with this robot that demonstrate the various component technologies. This is followed by a summary and concluding remarks.

11.2 NAVIGATION SYSTEM OVERVIEW

Upon viewing images of the Martian landscape (see Figure 11.1), one would agree that the terrain could be difficult to traverse even for a human driver of an off-road vehicle. The difficulty of the problem increases by orders of magnitude for an autonomous robotic rover. Nonetheless, human driver performance is a worthy goal to strive for in the design of a rover navigation system. In our design, we exploit the fact that fuzzy logic provides a viable means for endowing a computing system with human-like algorithmic reasoning capabilities. In part, we have sought to develop fuzzy inference systems for navigation that emulate human judgement and reasoning as derived from off-road driving heuristics [1] and loose analogies to rating systems used by rock climbers to assess the difficulty of traversing rough terrain [2].

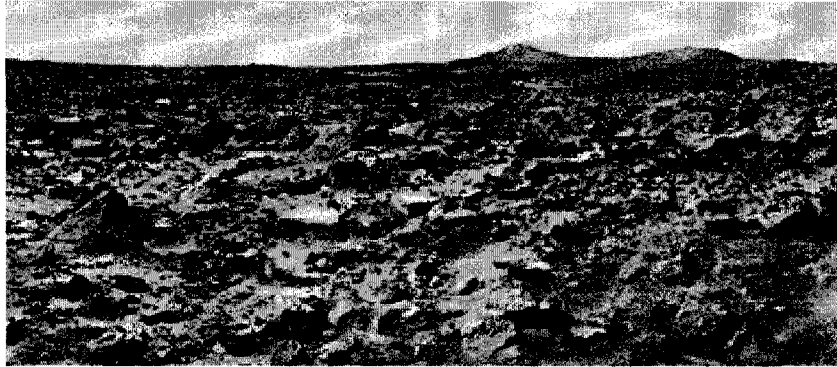


FIGURE 11.1 Mars Pathfinder Landing Site, 1997.

The safe navigation system is comprised of the various modules and components shown in Figure 11.2. With the exception of the low-level rover motion control system, each component is implemented using soft computing techniques — primarily fuzzy reasoning and control along with artificial neural networks, embedded within a behavior-based structure. The system consists primarily of modules dedicated to rover safety reasoning and strategic navigation control. These are accompanied by associated perception and actuation functionality. The safety reasoning module focuses on vehicle survivability and health, while the strategic navigation module focuses on mission and goal-directed motion from place to place.

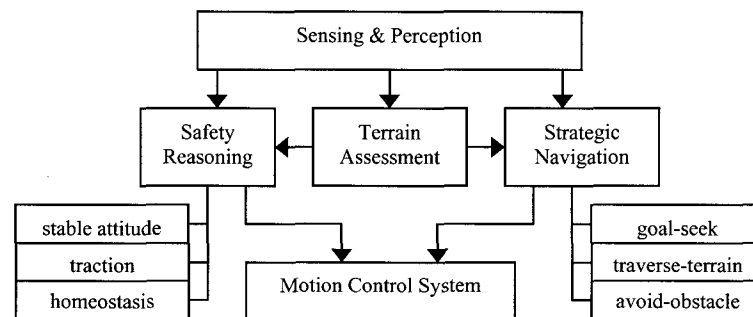


FIGURE 11.2 Modular System Diagram.

11.2.1 Fuzzy Behavior-Based Structure

We have adopted a fuzzy behavior-based approach [3] for implementation of the knowledge-based reasoning and control components. The architectural design is based on the premise that autonomous navigation functionality can be decomposed into a finite number of special-purpose task-achieving and decision-making behaviors. The basic building block, then, of the navigation strategy is a *behavior*. A behavior represents a mapping, from perceptions or goals to actions or decisions, aimed at achieving a given desired objective. That is, behaviors may be of two general types: control behaviors and decision behaviors. Fuzzy control behaviors are encoded as fuzzy rule-bases with distinct control policies governed by fuzzy inference. The control behaviors are typically simple and self-contained behaviors that serve a single purpose while operating in a reactive (non-deliberative) or reflexive (memoryless) fashion. Within each control module, fuzzy control behaviors perform nonlinear mappings from different subsets of the available sensor suite to set-points for common actuators. If X and U are input and output universes of discourse of a behavior with a rule-base of size n , the usual fuzzy IF-THEN rule takes the following form

$$\text{IF } x \text{ is } C_i, \text{ THEN } u \text{ is } A_i \quad (11.1)$$

where x and u represent input and output fuzzy linguistic variables, respectively, and C_i and A_i ($i = 1 \dots n$) are fuzzy subsets denoting linguistic values of x and u , which represent possible *conditions* and *actions*. In our case, the input x refers to sensory data; u refers to motion control variables that effect rover translation and rotation. The control variables serve as set-points for low-level classical PID motor controllers. In general, the rule antecedent consisting of the condition “ x is C_i ” could be replaced by a compound fuzzy proposition consisting of conjunctions, disjunctions, or complements of similar propositions. Similarly, the rule consequent consisting of the action “ u is A_i ” could be composed of multiple rule-base output propositions. Equation (11.1) represents a typical rule that expresses the actions taken by an expert human driver based on the prevailing conditions.

The control behaviors can be executed individually or concurrently to produce intelligent behavior for goal-directed navigation. Concurrent execution of fuzzy-behaviors is facilitated by fuzzy decision-making modules, which combine the individual capabilities by implementing a fuzzy set theoretic approach to inferring control gains and computing control inputs for the rover. Within each decision module, fuzzy decision behaviors map perceptual and goal information to appropriate gains based on the current situation or context. Reasoning is governed by rules of the following form

$$\text{IF } x \text{ is } S_k, \text{ THEN } w \text{ is } G_k \quad (11.2)$$

where x and w are fuzzy linguistic variables that represent sensor/goal data and control behavior gains, respectively. Here, S_k and G_k are fuzzy subsets of x and w , which represent possible navigational *situations* and adjustable *gains*.

Implementation details of each component are presented in the following sections. In the next section, we discuss relevant rover health and safety issues. We then describe how fuzzy logic can be applied to provide an intrinsic safety cognizance and a capacity for reactive mitigation of navigation risks. Having described how a nominal level of safety assurance can be achieved, we move on in subsequent sections to discuss higher-level cognitive components of the system that provide the strategic navigation capabilities necessary to perform mission- and goal-directed tasks.

11.3 FUZZY LOGIC-BASED ROVER HEALTH AND SAFETY

Built-in safe operation and health cognizance are essential for autonomous traversal through challenging terrain over extended time and distance. In many existing systems [4, 5], it is common to consider basic monitoring of individual hardware components for proper operation, but without explicit autonomous reaction or counter-action by the rover. Efficient management of on-board resources, such as power and science data storage capacity, and regulation of energy and internal temperature are common concerns for maintaining vehicle health [5-7]. In addition to vehicle health, operational safety is of primary importance. Navigation systems have also been developed which account for some measure of risk mitigation with respect to accidental damage (as due to tip-over) and/or vehicle entrapment [8, 9]. However, few field mobile robot systems have been reported in the literature that feature efficient implementation of both active vehicle health *and* safety countermeasures.

11.3.1 Health and Safety Indicators

The ability of a system to provide substantial safety countermeasures depends upon its capacity for assessing vehicle status with respect to the operating environment. Various observable states, events, and

terrain features can be considered for on-line assessment of a rover's operational status. Table I lists a number of possible health and safety indicators (HSIs) associated with rover on-board subsystems, which convey some aspect(s) of rover operational well-being as it relates to safe terrain traversal. At any given moment, the amount of power available to a rover system is perhaps the strongest indicator of its operational health. Solar energy is the primary power source for planetary rovers, although some systems have the luxury of rechargeable batteries. The attitude (pitch and roll) of the vehicle chassis can be monitored in order to avoid instabilities associated with ascent/descent of slopes, traversal of rocky terrain, and turning within vehicle curvature constraints. In addition to surface irregularities, the type and condition of the terrain surface provide clues for safety assessment. Human automobile drivers are able to perceive certain road conditions (e.g. oil slicks, pot-holes, and ice patches) as measures of safety, which can be reacted to in order to reduce the risk of potential accidents. In a similar manner, rover potential safety can also be inferred and reacted to based on knowledge of the terrain type or condition. Wheel-soil interactions are important mobility considerations in natural terrain. Excessive wheel slip reduces the effective traction that a rover can achieve and, therefore, its ability to make significant forward progress (not to mention the dramatic effect it can have on the accumulation of errors in estimated position and orientation over distance and time). On soft soils, such as sand, excessive wheel slip can often lead to wheel sinkage and eventual entrapment of the vehicle. Unfortunately, wheel slip and sinkage are often difficult to measure and estimate in a simple manner. Some progress has been made, however, in developing statistical estimation approaches for planetary rovers [10]. One simple approach involves the detection of drive motor stall via current sensing. A detected stall condition for one or more drive motors could be indicative of sinking, trapped, or stuck wheels. However, additional reasoning beyond speculation of the possible causes of a stalled motor would likely be necessary to assess the actual vehicle status. Other HSIs can be considered that are related to critical internal environment conditions such as temperatures of hardware components that are sensitive to thermal variations. In addition, general dynamic and kinematic states can be monitored for compliance with vehicle mechanical capabilities and constraints.

TABLE 11.1 Rover Health and Safety Indicators.

Health	Safety
Available power	Chassis attitude
Component failure or anomaly	Terrain type or condition
Component temperature	Wheel slip and sinkage
Drive motor stall	Dynamic/kinematic compliance

Ultimately, a comprehensive autonomous vehicle health and safety system is desired to increase rover survivability. Perhaps consideration of all items in Table I would make this possible, but such complete observability is rare in practice. To this end, we have concentrated on providing some of the elements necessary to approach the ultimate goal. As a baseline set of HSIs, we have considered chassis attitude, terrain type and condition, and available power.

The safety module will also incorporate a reasoning approach to homeostatic regulation of on-board resources. That is, the addition of automated mechanisms for self-regulation of internal operating condition is planned. A capability such as this is analogous to self-regulating functions provided by parts of human or animal physiology. An example of how this can be done is discussed in [11], where a homeostatic control approach for mobile robots is proposed based on analogy with the mammalian endocrine system. In that work, internal sensing is used to stimulate behavioral reactions through gain modulation and parameter adjustment, which contribute to regulation of energy and internal temperature. In our navigation system, this can be achieved through rover speed modulation and adjustment of relevant fuzzy set membership function parameters, to contribute to power efficiency and thermal regulation. A related approach applied to planetary rover prototypes is described in [6]. Reactions to power and internal temperature threshold violations are automatically invoked in response to internal sensing. The

reactions consist of halting rover motion to cool down or recharge batteries via solar panels, and activating internal heaters to warm up when necessary.

At this stage of development, the safety module employs concise fuzzy systems that provide autonomous reasoning to facilitate maintenance of stable vehicle attitude (pitch and roll) and wheel traction on rough terrain. The system employs off-road driving heuristics to facilitate avoidance of hazardous vehicle configurations and excessive wheel slip. In each case, our system is designed to produce safe speed recommendations associated with the current perception of the safety status of the rover. In the following, we discuss the associated soft computing solutions.

11.3.2 Stable Attitude Control

For indoor mobile robots, mobility and navigation problems can often be addressed in two dimensions since the typical operating environments consist of flat and smooth floors. In sharp contrast to this, mobility and navigation problems for outdoor rough terrain vehicles are characterized by significantly higher levels of difficulty. This is due to the fact that complex motions in the third dimension occur quite frequently as the vehicle traverses undulated terrain, encountering multi-directional impulsive and resistive forces throughout. The problem is more pronounced for vehicles with more or less rigid suspensions than it is for vehicles with articulated chassis. In any case, sufficient measures must be taken to maintain upright stability of the vehicle in both static and dynamic configurations.

For safety monitoring, the rover is outfitted with a two-axis inclinometer/tilt-sensor to measure pitch and roll. It is model CXTA02, manufactured by Crossbow Technology, Inc., which features $\pm 75^\circ$ range and 0.05° resolution. In this case, perhaps the simplest approach is to stop rover motion when either axis senses tilt beyond a critical threshold. In a few instances this may be sufficient. More often than not, however, dynamic effects such as momentum will quickly defeat the simplest approach and cause the rover to reach marginal stability (a point at which the vehicle begins to tip over), or worse yet, to actually tip-over. Even though planetary rovers are typically driven at low speeds (e.g. maximum average speed of ~ 0.3 m/s), more sophistication is required beyond binary threshold reactions. We have elected to formulate a strategy in which the recommended safe speed for the rover is proportionately modulated in reaction to changes in attitude (pitch and roll). When the rover travels on a relatively level surface, a maximum safe speed is recommended. As pitch and/or roll approaches extremes near marginal stability, gradual reductions in safe speed are recommended (including the stop condition). At attitudes between these extremes, recommended safe speeds are computed by interpolation via fuzzy sets and logical inference.

By considering various off-road driving heuristics for traversing rock fields, ravines, and hills (up-, down-, and side-hill), a set of fuzzy logic rules is formulated to maintain stable rover attitudes for safe navigation. Fuzzy subset partitions and membership function definitions for pitch and roll are derived based on subjective assessment of the problem. Pitch is represented by five fuzzy sets with linguistic labels {NEG-HIGH, NEG-LOW, ZERO, POS_LOW, POS-HIGH}, while roll is partitioned using three fuzzy sets with linguistic labels {NEG, ZERO, POS}. Here, positive and negative are abbreviated by “pos” and “neg”, respectively. Bounds on the universe of discourse for attitude measurements are chosen in accordance with the rover stability constraints and the level of acceptable risk. The rules and input membership functions for the stable attitude control component are shown in Figure 11.3. As is typical in fuzzy control systems, the membership functions, used to express uncertainty in the variables of each system component, take on triangular and/or trapezoidal shapes.

Fifteen fuzzy logic rules are employed to map the range of stable attitudes to safe driving speed recommendations. In addition to these rules, a crisp rule is applied to handle the extreme cases when marginal stability is reached and the safest reaction is to stop the motion. However, in contrast to the binary threshold scheme, as marginal stability is approached the rover speed is smoothly decreased to near-zero due to the interpolation provided by the fuzzy logic rules.

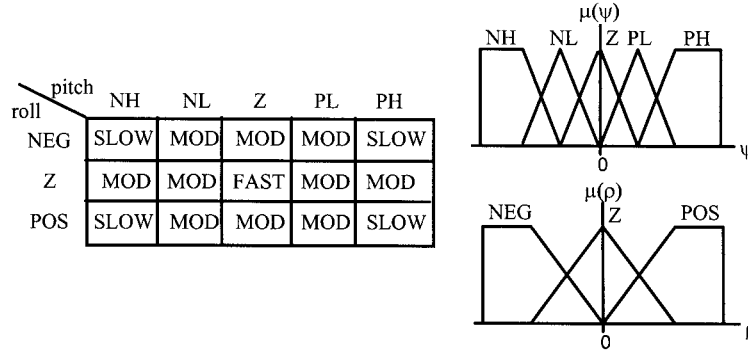


FIGURE 11.3 Rules and input membership functions for stable attitude control.

11.3.3 Traction Management

In the absence of some measure of control, wheeled vehicles are prone to loss of traction under certain conditions. On dry paved roads, traction performance is perhaps maximal for most wheeled vehicles due to the high coefficient of friction/adhesion between the road and tread (whether rubber or metal as in the case of some rover wheels). On off-road terrain, however, a variety of surface types are typically encountered including sand, gravel, densely packed soil, ice, mud, and so on. Based on current knowledge about the surface of Mars, rovers may encounter additional types of hard and soft surfaces on which rover wheels are susceptible to slippage. As mentioned above, loss of traction due to excessive wheel slip can lead to wheel sinkage and ultimately, vehicle entrapment. Frequent loss of traction during a traverse from one place to another will also detract significantly from the ability to maintain good position estimates. To improve mobility and navigation performance of rovers, a mechanism for regulating or minimizing wheel slip is highly desirable.

The problem of traction control is not new. It is a common problem in automobile and general transportation vehicle design with a variety of effective solutions. In many cases, solutions are derived from analyses based on the following equation for wheel slip ratio, λ , which is defined non-dimensionally as a percentage of vehicle forward speed, v :

$$\lambda = \left(1 - \frac{v}{r_w \omega_w} \right) * 100 \quad (11.3)$$

Here, r_w is the wheel radius and ω_w is the wheel rotational speed. Equation (11.3) expresses the normalized difference between vehicle and wheel speed. Therefore, when this difference is non-zero, wheel slip occurs. The objective of traction control is to regulate λ to maximize traction. This is a relatively straightforward regulation task if v and ω_w are observable. Wheel speed is typically available from shaft encoders or tachometers. However, it is often difficult to measure the actual over-the-ground speed for off-road wheeled vehicles. The problem is further complicated by nonlinearities and time-varying uncertainties due to wheel-ground interactions. Despite this, effective solutions have been found for automotive applications. In fact, fuzzy logic is a common tool for anti-lock (deceleration) and anti-slip (acceleration) control [12-15]. In these cases, measurement of v is facilitated by the even surface on which the vehicle travels. For example, in [11] an accelerometer is used to measure vehicle speed and the slip ratio is estimated based on deceleration of the four wheels. In [13], the measurement of vehicle speed is facilitated by the use of magnetic markers alongside the road in an intelligent highway automation

system. In this case, the vehicle speed is measured according to travel time between markers. For application to an electrically-driven locomotive, the solution in [14] makes use of a model of the friction-slip relationship, which is fixed for the wheel-rail interaction. On outdoor terrain, the friction-slip relationship varies with surface type. In large part, the available solutions are not directly transferable to off-road vehicle applications for which the terrain is uneven as opposed to being relatively flat, as is the case for automobiles and locomotives.

The use of an accelerometer to measure off-road vehicle speed is problematic since the gravity effects of traversing longitudinal and lateral slopes will interfere with the measurement. For an accelerometer used to measure horizontal acceleration, any off-horizontal vehicle tilt will be sensed as a change in acceleration; as a result, the integrated velocity will be in error. This is realized in [16] where an alternative traction control concept for rovers is considered. In that case, a non-driven “free wheel” is proposed for measuring actual vehicle speed. Another promising solution was proposed for rovers with an articulated chassis, which enables active control of the vehicle center of gravity. For those vehicles, the use of accelerometers in concert with rate gyroscopes is suggested [17].

In our work, we have elected to take a simple linguistic approach that does not rely on accurate sensing of vehicle speed. Instead, visual perception of terrain surface type is used to infer an appropriate speed of traversal. Results from traction tests performed on the actual rover are used to determine appropriate speeds for a range of potential surface types. In particular, the rover is tested on different terrain surfaces (e.g., sand, gravel, densely packed soil, etc) to determine the maximum speeds achieved before the onset of wheel slippage. Given this information, commanded vehicle speed can be modulated during traversal based on visual classification of the terrain surface type just ahead of the rover. This is analogous to the perception-action process that takes place when a human driver notices an icy road surface ahead and decelerates to maintain traction. For the rover, such speed modulation allows management of traction by mitigating the risk of wheel slippage.

Given the results of actual traction tests, the formulation of fuzzy rules to achieve speed modulation is relatively straightforward. The success of the traction management approach depends more heavily on the ability to perceive and classify the various terrain surface types. The problem of off-road surface type identification would be quite formidable for systems equipped with only proximity sensors, range-finders, and/or tactile probes. However, visual image-based classification has been found to be particularly promising [18]. We will now describe an artificial neural network solution to this problem that provides qualitative information about the expected surface traction ahead of the rover. This information is used to infer tractive rover speeds via fuzzy inference.

11.3.3.1 Neuro-Fuzzy Solution

Distinct terrain surfaces reflect different textures in visual imagery. The ability to associate image textures to terrain surface properties such as traction, hardness, or bearing strength has clear benefits for safe autonomous navigation. To provide this capability, we make use of an on-board camera pointed such that its field of view (FOV) covers an area on the ground in front of the rover. In this way, the projected image provides a downward looking view of the surface as illustrated in Figure 11.4a. Using a neural network (Figure 11.4b), texture analysis is performed on image data acquired by the camera. That is, a neural network classifier, trained to associate texture with several surface types, provides the information needed to make any necessary adjustments to wheel speed in order to maintain traction on the classified surface. Based on typical surfaces that the rover may encounter, three texture prototypes are selected: sand, gravel, and compacted soil (Figure 11.5).

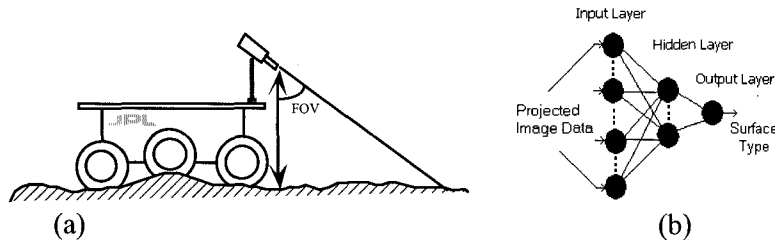


FIGURE 11.4 (a) Camera mounted on rover; (b) Neural network for surface classification.

The method proceeds as follows. Assuming the section of the image just ahead of the front wheels is free of obstacles, a set of 40x40 pixel image blocks is randomly selected from a camera image of size 320x280 pixels. To reduce the large data dimensionality inherent in typical vision-based applications, a filtering step is performed. This permits effective extraction of features embedded in the surface image data set in real time. The image blocks are normalized to compensate for lighting variations and the data is used to train the neural network classifier. After training the network on typical image data representing different surface prototypes, we utilize it to classify the surface types during run-time.

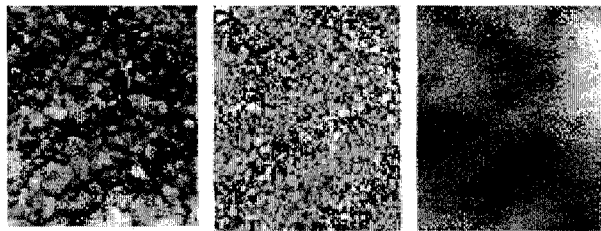


FIGURE 11.5 Terrain surface texture images: gravel, sand, compacted soil.

The neural network is trained to provide texture prototype outputs in the unit interval $[0, 1]$, with 0 corresponding to surfaces of very low traction (e.g., ice) and 1 corresponding to surfaces of high traction (e.g., dry cement). This is a design decision motivated by a desire to establish some correlation to actual wheel-terrain coefficients of friction. In this way, we can make a qualitative association between neural network output and expected traction in front of the rover. In the sequel, we will refer to the texture prototype output as the *traction coefficient*, denoted by C_t .

Wheel-terrain friction coefficients for a variety of tread and surface types are widely published in the literature on vehicle mechanics. However, published friction coefficients for identical tread and surface types vary from source to source. This is due to the fact that measured values depend heavily on the variety of tests and conditions from which they were generated. Nevertheless, common ranges of friction coefficients for given tread and surface types are widely agreed upon. The following are typical estimates of the friction coefficient for rubber tires on various surfaces: icy road/snow (0.1), sand (0.3), slippery/wet road (0.4), hard unpaved road (0.65), grass (0.7), dry paved road (0.8-1.0).

Given the uncertainty in associating exact friction coefficients with certain terrain surface types, and the loose correlation provided by the traction coefficient, we elect to reason about traction using fuzzy logic. The range of traction coefficients, $[0,1]$, obtained from the neural network classifier is partitioned using three fuzzy sets with linguistic labels {LOW, MEDIUM, HIGH}. Triangular membership functions are used which are equally distributed throughout the universe of discourse. Based on these definitions, the following simple fuzzy logic rules are applied to manage rover traction on varied terrain:

- IF C_t is LOW, THEN v is SLOW.
- IF C_t is MEDIUM, THEN v is MODERATE.

- IF C_t is HIGH, THEN v is FAST.

Here, membership functions for the rover speed v are defined over the range of tractive speeds that result from traction tests on various surface types. Note that the neural network can be trained to map its inputs directly to the actual range of tractive speeds (rather than the range of C_t). However, in this neuro-fuzzy approach, fuzzy inference serves to accommodate uncertainties in both the surface classification and the subsequent specification of tractive speed.

In summary, the stable attitude and traction management components of the safety module combine to provide active countermeasures to potential vehicle tip-over and excessive wheel slip. The minimum of the rover speeds inferred by the two components is issued as the safe speed recommendation v_{safe} . The interface between the safety module and the strategic navigation module is depicted in Figure 11.6. As indicated by the diagram, safe speeds recommended by the safety module are compared to the strategic speed recommendations, and the safest speed is issued as the commanded set-point for the motion control system. The determination of safe rover speed is independent of the behavior fusion process (discussed later) that produces the strategic navigation speed. This allows recommended safe speeds to override strategic speeds, if necessary, to ensure vehicle safety. This is also the approach taken in [19] where it is asserted that distributing speed control across all behaviors makes it difficult to ensure that the interactions will yield a safe speed.

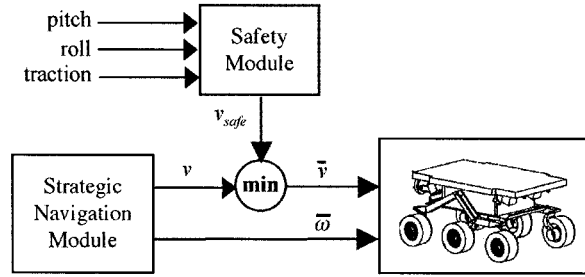


FIGURE 11.6 Safety and strategic navigation module interface.

11.4 FUZZY TERRAIN-BASED NAVIGATION

In dealing with day-to-day processes, humans make subjective decisions based on qualitative information. Their perception of processes is based on qualitative, rather than quantitative, assessments obtained from imprecise and approximate measurements. The human control strategy for a process typically consists of simple, intuitive, and heuristic rules based on prior experience that are brought to bear to affect the process. For instance, in the process of driving a car, the human driver turns the steering wheel to the right if the car veers too far to the left, and vice versa. The driver intuitively determines the degree of course correction based on driving experience, rather than resorting to mathematical modeling and formulation of the process. His actions are based on how far from the lane the car has moved, and on how fast the car is moving. Similarly, the driver adjusts the speed of the car based on his subjective judgement of the road conditions, e.g., the car speed is decreased in off-road driving on a bumpy and rough terrain but is increased on a smooth and flat surface. This human control strategy exhibits characteristics of reactivity, set-point tracking, and regulation, all perceptually guided by qualitative situational assessments. As mentioned earlier, it is highly desirable to capture the essence of the tight perception-action control loop exhibited by human drivers for implementation in autonomous navigation strategies for planetary rovers.

To develop intelligent navigation controllers, we formulate simple and intuitive fuzzy logic rules that capture the attributes of human-driver reasoning and decision-making. Robust navigation behavior in practical rover systems can be achieved when perception uncertainty and actuator imprecision is accommodated by the rover control system. Such is the case when fuzzy logic control and decision systems are employed. That is, the linguistic values in the rule antecedents can be chosen to convey the imprecision associated with on-board sensor measurements, while those in the rule consequents can represent the vagueness inherent in the reasoning processes and the imprecision inherent in actuator operation. Having developed a number of desired navigation behaviors in this way, one may rely upon the computational mechanisms of fuzzy logic to provide robust inference and approximate reasoning under practical uncertainties. The operational strategies of the human expert driver then, can be transferred via fuzzy logic tools to the robot navigation strategy in the form of several fuzzy behaviors. The main advantages of such a navigation strategy lie in the ability to extract heuristic rules from human experience and to obviate the need for an analytical model of the process. To complement this methodology, we have developed soft computing solutions for robust qualitative assessment of terrain traversability, which permits further advancement toward achieving human driver performance. Our approach is enabled by intelligent visual perception using terrain imagery captured by cameras on-board the rover.

11.4.1 Visual Terrain Traversability Assessment and Fuzzy Reasoning

Outdoor navigation systems for autonomous field mobile robots must consider terrain characteristics in order to support safe and efficient traversal from place to place. Two important attributes that characterize the difficulty of a terrain for traversal are the slope and roughness of the region. In current methods of terrain assessment [20-24], terrain traversability is defined as an analytical function of the terrain slope and roughness in the region local to the vehicle. The slope is determined by finding the least-squares fit of a geometric plane covering the region, while the roughness is calculated as the residual of the best-plane fit. Once the traversability of each region is evaluated, a traversable path for the robot to follow is then constructed. These analytical representations of the terrain traversability rely on accurate interpretation of the sensory data, as well as an exact mathematical definition of the traversability function. Here, we present an alternative approach based on fuzzy reasoning. Real-time terrain assessment is achieved by computing physical properties of the terrain (such as roughness and slope) using data provided by stereo cameras mounted on the rover. The terrain properties are then used to *infer* traversability according to a recently introduced measure called the *Fuzzy Traversability Index* [25, 26]. The Fuzzy Traversability Index is a simple measure for quantifying the suitability of a natural terrain for traversal by a mobile robot. It can be inferred from knowledge of physical terrain properties, but it also depends on the properties of the robot mobility mechanism, which determine its hill and rock climbing capabilities. In order to quantify the roughness and slope of a region, image processing algorithms are applied for terrain feature extraction as described below.

11.4.1.1 Terrain Roughness Extraction

During navigation, images of the viewable scene are periodically captured by the rover vision system. An algorithm is applied to a pair of stereo camera images that determines the sizes and concentration of rocks/ditches in the viewable scene. These parameters are used to infer terrain roughness, β , which is represented by fuzzy sets with linguistic labels {SMOOTH, ROUGH, ROCKY}. Equally spacing trapezoidal membership functions are used.

The rock size and concentration parameters are represented in terms of a two-parameter vector $r = [r_{\text{small}}, r_{\text{large}}]$, where r_{small} denotes the concentration of small-sized rocks and r_{large} represents the concentration of large-sized rocks contained within the image. In order to compute these parameters, a horizon-line extraction program is run that identifies the peripheral boundary of the ground plane. This, in effect, recognizes the point at which the ground and the landscaped backdrop intersect. The algorithm

then identifies target objects located on the ground plane using a region-growing method [27]. In effect, target objects that differ from the ground surface are identified and counted as rocks for inclusion in the roughness assessment. The denser the rock concentration, the higher the calculated roughness of the associated region. Figure 11.7 shows an example output of the rock identification algorithm.

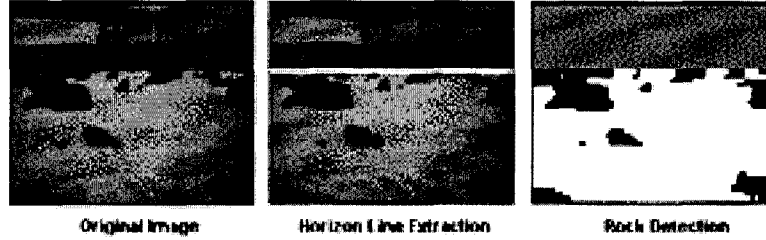


FIGURE 11.7 Visual terrain roughness extraction.

To determine the number of small and large-sized rocks contained within the image, the number of pixels that comprise a target object are first enumerated. Those targets with a pixel count less than a user-defined threshold are labeled as belonging to the class of small rocks and those with a count above the threshold are classified as large rocks. The threshold is determined based on the mechanical characteristics of the rover, such as wheel size, wheel-base, body height, and so on. This defines fuzzy sets with linguistic labels {SMALL, LARGE}, which represent the rock sizes, R_s . All such labeled target objects are then grouped according to their sizes in order to determine the small and large rock concentration parameters. These values are then used to populate the two-parameter vector r , which is characterized by fuzzy sets with linguistic labels {FEW, MANY} and used as input for the following fuzzy logic rules, where R_c represents the rock concentration:

- IF R_c is FEW AND R_s is SMALL, THEN β is SMOOTH.
- IF R_c is FEW AND R_s is LARGE, THEN β is ROUGH.
- IF R_c is MANY AND R_s is SMALL, THEN β is ROUGH.
- IF R_c is MANY AND R_s is LARGE, THEN β is ROCKY.

The terrain roughness is thus derived directly from the rock size and concentration parameters of the associated image scene.

11.4.1.2 Terrain Slope Extraction

Slope characterizes the average incline/decline of the ground surface to be traversed. To obtain the surface slope, an innovative approach is utilized to obtain depth information from two uncalibrated cameras. The process involves training a neural network to learn the relationship between slope and correlated image points that lie along the horizon-line.

Given a pair of camera images, the algorithm first locates correlated points by determining the position of the largest rocks located along the horizon-line and centered within both images (Figure 11.8). Once these points are extracted, the pixel locations in the two images are used as inputs to a trained neural network for slope extraction.

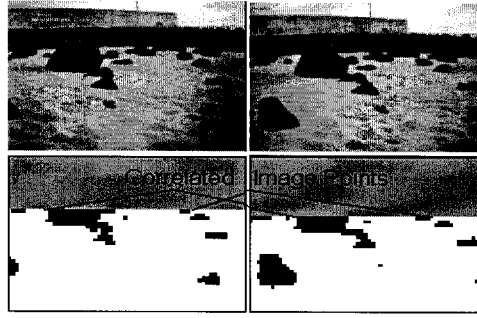


FIGURE 11.8 Determination of correlated image points.

Using our algorithm, we wish to find a relationship between corresponding image points located along the horizon-line and the slope of the viewable terrain. Initially, we train the network by finding a set of weights that will give us the desired slope output. We utilize a 3-layer feed-forward neural network with error backpropagation. In this process, we present a set of correlated image points and the corresponding slope value to the network. Given this input, the network will calculate the output, which is then compared with the desired slope parameter. The difference between the network slope output and the desired slope value is then used to change the network weights, thus minimizing the network's error. In this way, the network can learn the desired relationship between correlated image points and slope.

Our network has four input nodes corresponding to the image positions of the correlated points in the two images, and one output node corresponding to the terrain slope parameter. The hidden layer has two processing elements. After training the network on typical imagery data representing different positive and negative sloped examples, we utilize it to extract the slope during run-time. The network output provides the terrain slope parameter, α , whose magnitude is then converted into the linguistic representation {FLAT, SLOPED, STEEP}, with membership functions similar to those defined for β .

11.4.1.3 Fuzzy Inference of Terrain Traversability

Once the slope and roughness parameters of the region are determined from the camera images, the Fuzzy Traversability Index, τ , is inferred and used to classify the ease of terrain traversal. The index is represented by three trapezoidal fuzzy sets with linguistic labels {LOW, MEDIUM, HIGH}. The Fuzzy Traversability Index is defined in terms of the terrain slope α and the terrain roughness β by a set of simple fuzzy logic relations summarized in Figure 11.9. Observe that this approach to terrain assessment gives an intuitive, linguistic definition of terrain roughness and traversability as used by a human observer, in contrast to the mathematical definitions (as the residual of the least-squares plane fit and as analytical functions of slope and roughness) used previously [20-24]. This representation has the advantage of being robust and tolerant to uncertainty and imprecision in measurements, and in the interpretation of sensor data. It conveys sufficient qualitative information about the terrain to permit intelligent assessment of traversability. In addition, it can be easily extended to include consideration of additional terrain features in the reasoning process.

		α		
β		FLAT	SLOPED	STEEP
	SMOOTH	HIGH	MED	LOW
	ROUGH	MED	LOW	LOW
	ROCKY	LOW	LOW	LOW

FIGURE 11.9 Fuzzy rule table for traversability index.

11.5 STRATEGIC FUZZY NAVIGATION BEHAVIORS

The robot navigation strategy presented in this section is comprised of three simple motion behaviors: seek-goal, traverse-terrain, and avoid-obstacle. These behaviors operate at different perceptual resolutions. The fuzzy logic rules for the seek-goal behavior make use of *global* information about the goal position to make recommendations for rover speed and steering. The fuzzy logic rules for the traverse-terrain behavior incorporate the *regional* information about the terrain quality to produce recommendations for rover speed and steering. The fuzzy logic rules for the avoid-obstacle behavior utilize *local* information about en-route obstacles to generate the appropriate speed and steering recommendations. The output of each behavior is a recommendation over all possible control actions from the perspective of achieving that behavior's objective. Each control recommendation is represented by a fuzzy possibility distribution over the space of speed and steering commands. To facilitate behavioral rule formulation, the rule set for each motion behavior has been de-coupled into turn rules and move rules. In the final stage before commanding rover actuators, the individual fuzzy recommendations from the three behaviors are aggregated and defuzzified to yield crisp control inputs. This process of behavior fusion is facilitated by the use of weighting factors inferred from navigational contexts. The approach yields an autonomous navigation strategy for the rover that requires no *a priori* information (e.g. maps) about the environment. We will now describe in detail the individual fuzzy control behaviors and the behavior fusion approach to realizing goal-directed navigation.

11.5.1 Seek-Goal Behavior

The problem addressed in this section is to navigate a rover on a natural terrain from a known initial position to a user-specified goal position. The rover control variables for this behavior are the translational speed v and the rotational speed ω . The vehicle speed v is represented by four fuzzy sets with linguistic labels {STOP, SLOW, MODERATE, FAST}. Triangular membership functions are defined which are equally distributed throughout a range of allowable rover speeds. Similarly, the rover turn rate ω is represented by five fuzzy sets with linguistic labels {FAST-LEFT, SLOW-LEFT, ON-COURSE, SLOW-RIGHT, FAST-RIGHT}, defined by equally spaced triangular membership functions over a range of allowable turn rates.

The fuzzy navigation rules for the seek-goal behavior direct the rover to initially perform an in-place rotation toward the goal to nullify the heading error, ϕ , which is the relative angle by which the rover needs to turn to face the goal directly. Once the rover is aligned with the goal direction, it then proceeds toward the goal position. A similar rule set can also be formulated for robots that cannot perform in-place rotation.

The fuzzy rules for rover rotational motion are listed below, where the heading error input ϕ is represented by five fuzzy sets with linguistic labels {GOAL-FAR LEFT, GOAL-LEFT, GOAL-HEAD ON, GOAL-RIGHT, GOAL-FAR RIGHT}. The turn rules are followed by a list of fuzzy rules used for rover translational motion, where the position error input (goal distance) d is represented by four fuzzy sets with linguistic labels {VERY NEAR, NEAR, FAR, VERY FAR}. The universe of discourse for both ϕ and d is partitioned by an equal distribution of triangular membership functions.

- IF ϕ is GOAL-FAR LEFT, THEN ω is FAST-LEFT.
- IF ϕ is GOAL-LEFT, THEN ω is SLOW-LEFT.
- IF ϕ is GOAL-HEAD ON, THEN ω is ON-COURSE.
- IF ϕ is GOAL-RIGHT, THEN ω is SLOW-RIGHT.
- IF ϕ is GOAL-FAR RIGHT, THEN ω is FAST-RIGHT.

- IF d is VERY NEAR OR ϕ is NOT GOAL-HEAD ON, THEN v is STOP.

- IF d is NEAR AND ϕ is GOAL-HEAD ON, THEN v is SLOW.
- IF d is FAR AND ϕ is GOAL-HEAD ON, THEN v is MODERATE.
- IF d is VERY FAR AND ϕ is GOAL-HEAD ON, THEN v is FAST.

The first rule for translational motion keeps the rover stationary while it is correcting its heading. In the remaining translational motion rules, the rover is aligned with the goal direction and moves with a speed proportional to its distance from the goal.

11.5.2 Traverse-Terrain Behavior

This section presents fuzzy logic rules that use the Fuzzy Traversability Index to infer the vehicle turn rate and speed while moving on natural terrain. It is assumed that the robot can only move in the forward direction (i.e., reverse motion is not allowed). The visual sensor coverage area of the terrain region in front of the rover spans 180° . This sensor horizon is partitioned into three 60° sectors, namely: front, right, and left of the rover position at a sensing distance of up to 5 meters. The indices for the three regions, τ_f , τ_r , τ_l , are inferred in real-time from the values of terrain slope and roughness extracted by the on-board vision system. The fuzzy rules for determining rover steering based on the terrain traversability data are summarized in Figure 11.10a. The rule table in Figure 11.10b corresponds to steering behavior for obstacle avoidance (discussed below). These rules emulate the steering actions of the human driver during an off-road driving session.

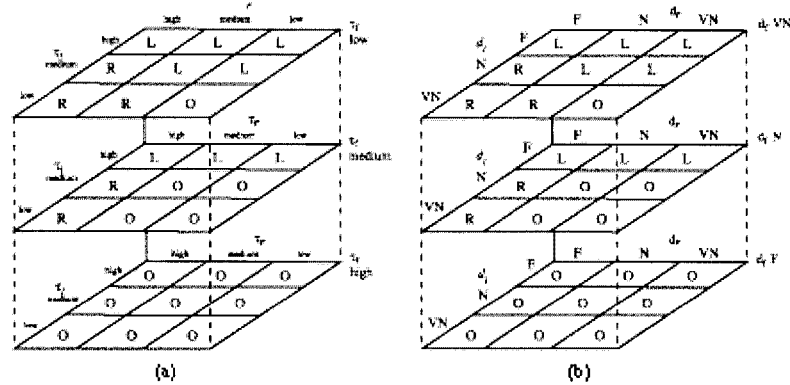


FIGURE 11.10 Turn rules for (a) traverse-terrain and (b) avoid-obstacle.

Examining Figure 11.10a, we see that a turn maneuver is not initiated when either the front region is the most traversable, or the right and left regions have the same traversability indices as the front region. Also, observe that the “preferred” direction of turn is chosen arbitrarily to be LEFT, i.e., when the rover needs to turn to face a more traversable region, it tends to turn left. The choice of LEFT instead of RIGHT is arbitrary, but selection of a preferred turn direction is essential to avoid the possibility that simultaneous left and right rotations can result in a no-turn recommendation even though there may be an impassable region directly ahead of the rover.

Once the direction of traverse is chosen based on the relative values of τ , the rover speed v can be determined based on the value τ^* of the traversability index τ in the *chosen region*. This determination is formulated as a set of two simple fuzzy logic rules for speed of traverse: IF τ^* is LOW, THEN v is STOP, and IF τ^* is MEDIUM, THEN v is SLOW. The effect of these rules is analogous to that of the human driver adjusting the car speed based on the surface conditions.

11.5.3. Avoid-Obstacle Behavior

In this section, fuzzy logic rules are presented which govern rover behavior based on the local information about en-route obstacles, such as large rocks. In general, obstacles may belong to any variety of mobility and navigation hazards such as extreme slopes, sand/dust-covered pits, crevasses, cliffs and otherwise unstable terrain. Also included are so-called negative obstacles such as ditches and craters, and their complements such as ridges and boulders. Rocks that are considered obstacles are those with sizes that exceed the obstacle-climbing threshold for which the rover is designed. In the case of the Mars rover *Sojourner*, the threshold was 1.5 wheel-diameters. Without loss of generality, we may refer to the general category of untraversable patches of terrain as navigation obstacles. This local obstacle information is acquired on-line and in real-time by the proximity sensors mounted on the rover. For space robotics applications, different types of proximity sensors can be used, ranging from low-resolution infrared sensors to high-resolution and longer-range laser detectors [29]. A wider range of options is available for use in more general mobile robot applications [30]. The range of reliable operation of proximity sensors is typically 20-50 cm, which is about an order-of-magnitude shorter than that of regional sensor coverage. Note, however, that precise measurement of the obstacle distance is *not* needed, because of the multi-valued nature of the fuzzy sets used to describe it.

In the present implementation, it is assumed that there are three groups of proximity sensors mounted on the robot facing the three different directions of front, right, and left. These sensors report the distances between the robot and the closest front obstacle d_f , the closest right obstacle d_r , and the closest left obstacle d_l within their ranges of operation. The three obstacle distances are continuously measured and updated during rover motion. The steering and speed rules for avoiding obstacles use this local information to maneuver the robot around the obstacles and to avoid potential collisions. Each obstacle distance d_f , d_r , or d_l is represented by the three fuzzy sets with linguistic labels {VERY NEAR, NEAR, FAR}. Equally distributed trapezoidal membership functions are defined for each obstacle distance. Typically, different fuzzy set bounds are defined on the universe of discourse for the front obstacle distance and side (left and right) obstacle distances so that front and side collision detection will have different sensitivities.

The behavioral objectives of the obstacle avoidance rules are to direct the rover to: (a) turn to face a region with the least nearby obstacles, and (b) adjust its speed of motion depending on the distance to the closest front obstacle. The goal of the steering rule set is to steer the robot clear of all obstacles. This goal is accomplished by sensing the three obstacle distances and reacting according to the fuzzy logic rule sets summarized above in the Figure 11.10b. The following points are noted about the above steering rules. First, when d_f is FAR, i.e., the front of the rover is clear of obstacles, the rover will not collide with any obstacles and no corrective action needs to be taken. Therefore, the collision avoidance steering rules are activated only when the situation is otherwise. Second, observe that the “preferred” direction of turn is chosen to be LEFT, i.e., when the rover needs to turn to avoid an impending collision, it tends to turn left. The choice of LEFT instead of RIGHT is arbitrary, but selection of a preferred turn direction is essential to avoid the possibility that simultaneous left and right obstacles can result in a no-turn recommendation even though there may be an obstacle in front of the vehicle.

The speed rules for collision avoidance are very simple. Basically, the robot is required to slow down as it approaches the closest front obstacle. Again, note that when the front obstacle distance is FAR, collision avoidance is not activated and no corrective action needs to be taken. There are two fuzzy logic rules as follows: IF d_f is VERY NEAR, THEN v is STOP, and IF d_f is NEAR, THEN v is SLOW.

11.5.4. Fuzzy-Behavior Fusion

The decision-making process used to combine recommendations from multiple behaviors is commonly referred to as *behavior coordination* [3]. The most common approach is *behavior arbitration*, which employs a prioritization scheme wherein the control recommendation of only one behavior among several

competing behaviors is taken; while recommendations from the remaining behaviors with lower priorities are ignored. In contrast to this switching type of arbitration, we advocate using a more comprehensive blending scheme. The preferred coordination scheme permits more than one behavior to influence the resultant control action to the extent governed by variable gains or weighting factors assigned dynamically according to the prevailing context — a scheme referred to as *behavior fusion*. Behavior fusion is facilitated by fuzzy set theoretic computations, however, non-fuzzy implementations are also possible [8]. Thus, in the proposed approach, weight rules combine elemental behaviors, not through fixed-priority arbitration, but rather through a generalization of dynamic gains that are determined based on consideration of the situational status of the rover. The weight rules continuously update the behavior weighting factors during rover motion based on the prevailing conditions.

The gains or weighting factors s^w , t^w , and a^w represent the strengths by which the seek-goal, traverse-terrain, and avoid-obstacle recommendations are taken into account to compute the final control actions \bar{v} and $\bar{\omega}$. These weights are represented by two fuzzy sets with linguistic labels {NOMINAL, HIGH}. Three sets of decision rules for the respective motion behavior gains are listed below.

- IF d is VERY NEAR, THEN s^w is HIGH.
- IF d is NOT VERY NEAR, THEN s^w is NOMINAL.

- IF d is NOT VERY NEAR AND d_f is NOT VERY NEAR, THEN t^w is HIGH.
- IF d is VERY NEAR OR d_f is VERY NEAR, THEN t^w is NOMINAL.

- IF d is NOT VERY NEAR, THEN a^w is HIGH.
- IF d is VERY NEAR, THEN a^w is NOMINAL.

At each control cycle, the above sets of gain rules are used to calculate the three crisp weighting factors using the Center-of-Gravity (Centroid) defuzzification method. Note that with this defuzzification method, overlapping areas between adjacent truncated membership functions in the aggregated fuzzy set are counted twice. The resulting crisp weights are then used to compute the final control actions for the rover speed and turn rate.

Fuzzy recommendations from the seek-goal, traverse-terrain, and avoid-obstacle behaviors are weighted by the corresponding behavior gains prior to defuzzification, as shown in Figure 11.11. The weighted fuzzy outputs for the individual behaviors are aggregated into single fuzzy possibility distributions for both rover speed and turn rate. The final control actions for each cycle are computed using the Center-of-Gravity defuzzification method.

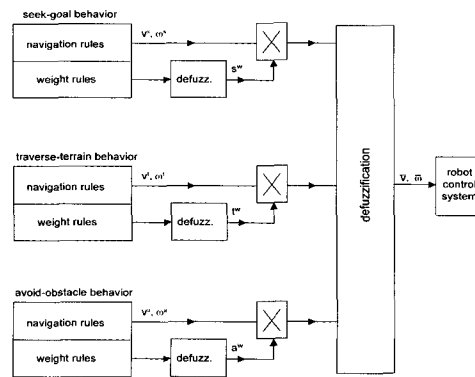


FIGURE 11.11 Fuzzy-behavior fusion.

11.6 ROVER TESTBED AND EXPERIMENTAL RESULTS

Field tests using the Pioneer AT (All-Terrain) rover are conducted on rough terrain near JPL (Pasadena, California) to test the reasoning and decision-making capabilities provided by the fuzzy logic navigation strategy. This commercially available rover is kinematically quite different from planetary rovers designed for Mars. Nonetheless, with certain enhancements it is suitable as a testbed for developing advanced technology and algorithms for infusion into flight rover navigation systems. The Pioneer AT rover, shown on the left of Figure 11.12, is enhanced with additional on-board processing capability, 8-input image multiplexer, a vision system for real-time terrain assessment, and a tilt sensor (mentioned in Section 11.3.2). The vision system consists of eight CMOS NTSC video cameras. Six cameras are mounted on a raised platform and used for terrain-based navigation. The right side the figure shows the physical layout of the camera platform used specifically to provide terrain imagery data. These six cameras are placed such that the lens centers are 740mm above the ground and the optical axis of each camera is tilted down by 8° . The intersecting origin of all cameras is centered above the support polygon formed by the rover wheel-ground contact points. In addition, the stereo baseline length is set to 500mm. This camera placement scheme provides the rover a viewable distance of $\sim 5\text{m}$ spanning a field of view of $\sim 180^\circ$. The remaining two cameras are mounted on a mast below the raised platform and pointed towards the ground for obstacle detection and surface type classification.

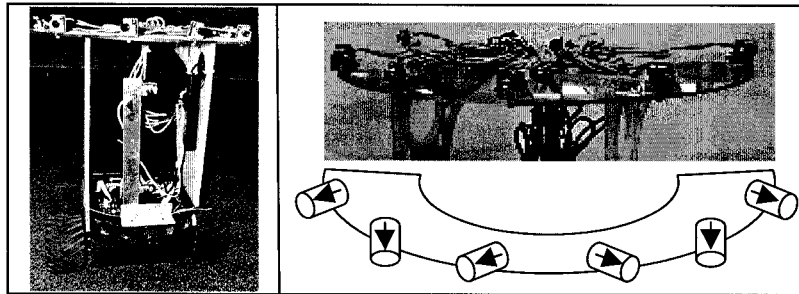


FIGURE 11.12 Enhanced Pioneer AT with terrain assessment vision system.

The processing power on-board the rover consists of a 333 MHz Pentium II processor housed in a CompactPCI chassis running the Linux Operating System. The system has also been tested using a laptop computer running Windows 95. Resident on the computer are the image processing algorithms and the fuzzy logic computation engine (written in the C language) used to calculate the translational and rotational speed commands issued to control the wheel motors. Using this hardware platform, rover field tests are performed outdoors in natural terrain. We shall now present field test and experimental results for the safety module and the strategic navigation module.

11.6.1 Safe Mobility

In this section, we describe two field tests and associated laboratory experiments performed to evaluate the effect of the safe attitude and traction components. The first test considers reactions to rover pitch and roll during traversal. The second test is concerned with mitigation of wheel slippage.

For the stable attitude test, an obstacle-free swath of undulated terrain is chosen. The rover is commanded to traverse the swath with and without the stable attitude component activated. Without active stable attitude management, the rover traverses the terrain at a nominally fast speed recommended by the strategic navigation system based on the fact that no significant obstacles are present. With active

attitude management, the rover traverses the terrain at various reduced speeds in response to changes in its pitch and roll according to the fuzzy logic rules in Figure 11.3. This reactivity reduces the risk of approaching marginal tilt stability, which leads to tip-over. It also enhances the ability of rigid-suspension vehicles (such as the Pioneer AT) to maintain wheel contact with the ground. A comparative effect of the stable attitude component is shown in Figure 11.13. The left picture corresponds to the test without active attitude management; it shows a case where the rear-right wheel loses contact with the ground. The right picture shows the rover at the same approximate location with all wheels making ground contact while actively modulating its speed to maintain stable attitude.

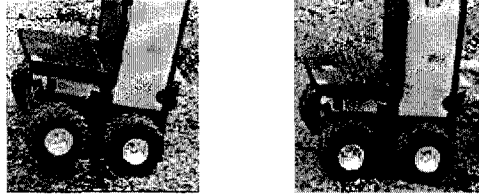


FIGURE 11.13 Comparative effect of stable attitude management.

To further illustrate the effect of safe attitude management, we exercise the component in a laboratory experiment where the rover traverses a swath of terrain for 10 meters. Synthetic attitude measurements are generated by sinusoidal functions of random amplitude to emulate changes in pitch and roll experienced on a hypothetical undulated and rough terrain. The amplitudes are uniformly distributed random numbers bounded by the maximum stable pitch and roll of the rover. It is assumed that the strategic navigation module recommends a constant normalized speed of 75% (of maximum allowable speed) throughout the traverse. The results of this experiment are shown in Figure 11.14 in plots of pitch, roll and v_{safe} (normalized) versus distance. The strategic speed is shown in the speed-distance plot as a dashed line. Observe that v_{safe} is modulated low in response to near-extreme attitudes. This is most apparent when both pitch and roll are simultaneously large in magnitude.

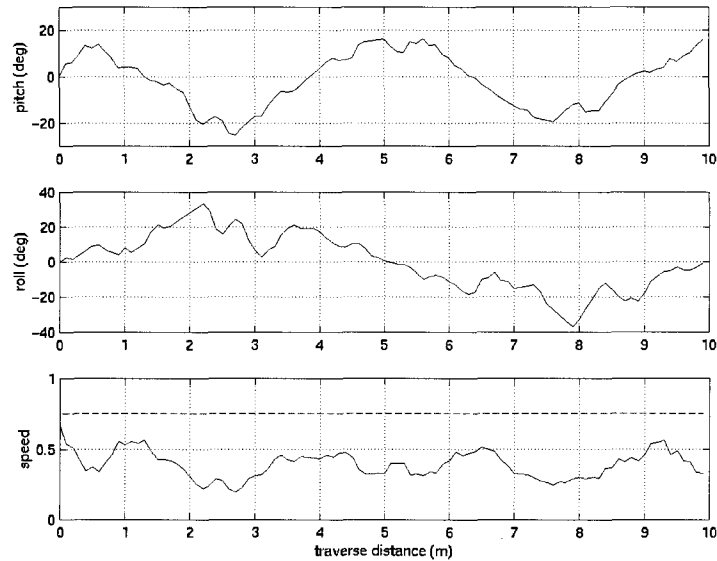


FIGURE 11.14 Speed modulation for attitude management.

To test safe traction management, a benign portion of terrain comprising two distinct surface types (hard compact soil and gravel) is chosen on which the rover will be susceptible to wheel slippage when traversing the surface transition at nominally fast speeds. The scenario is depicted in Figure 11.15 where the rover is about to transition from a hard compact soil to gravel surface. The rover is commanded to traverse the transition with and without the safe traction management component activated. Again, without active traction management, the rover traverses the terrain at a nominally fast speed. With active traction management, the rover reduces its speed upon encountering a surface of lower perceived traction (as classified by the vision-based neural network classifier described earlier) according to the fuzzy logic rules presented in Section 11.3.3.1. This reactivity mitigates the risk of excessive wheel slippage during transitions between, and traversal on, surfaces of different traction characteristics.



FIGURE 11.15 Rover approaching surface type transition.

To further illustrate the effect of the safe traction management, we exercise the component in a laboratory experiment where the rover traverses a 12 meter swath of terrain consisting of different surface types for which the traction coefficient C_t is 0.5 for 5m, 0.2 for 3m, and 0.9 for 4m. We assume, for the sake of discussion, that these values correspond to sand, gravel, and concrete, and that the surface texture camera has a ground surface view horizon out to 0.3m in front of the rover wheels. In this experiment, the strategic navigation module recommends a constant normalized speed of 80% throughout the 12m traverse. The result is shown in Figure 11.16 where the recommended rover speeds are plotted versus distance; the strategic speed is shown as a dashed line. Images of the three terrain surface types corresponding to distance are inset in the figure as well. As expected, changes in perceived traction result in reactive management of the safe speed recommended by the safe traction component to avoid the risk of excessive wheel slippage. Note that our laboratory experiment accounts for a reaction delay between classification of the surface type and the actual change in set-points for v_{safe} . Thus far, our tests have revealed that v_{safe} is consistently lower than the strategic speed, thus exhibiting the caution of the safety module in reaction to cognizance of vehicle safety and changing “road” condition.

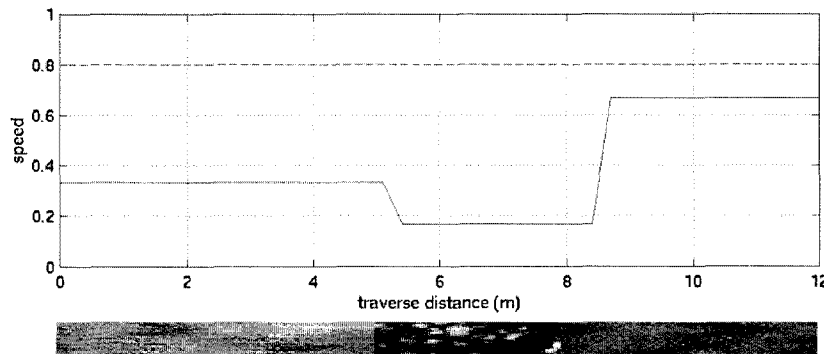


FIGURE 11.16 Speed modulation for traction management.

11.6.1 Safe Navigation

The strategic navigation module was also tested in the field. In this section, we present results of a point-to-point navigation run in natural terrain. To navigate from a starting position to a user-specified goal position, the rover employs three navigation behaviors — seek-goal, traverse-terrain, and avoid-obstacle. The goal position is located approximately 20m in front of the rover. Directly in-between the starting and the goal positions are two regions having low traversability — one region contains a highly sloped hill and the other contains a large cluster of rocks. Figure 11.17 shows the path traversed by the rover from its original starting position until it has autonomously reached the specified goal position using its on-board fuzzy logic navigation rules. The rover begins by first analyzing the traversability of the three partitioned 60° sectors (left, front, right) of the terrain located in front of the rover. The front and left sectors (which contain the large sloped hill) are found to have low traversability. The rover therefore turns toward the right sector, which is found to be highly traversable and proceeds to enter the safe region. Once in the safe region, the rover turns and navigates toward the goal, while ensuring that it is still physically located in the highly traversable sector; this corresponds to the last scene in the top row of images in Figure 11.17. Note that the viewpoint of the camera recording the path in Figure 11.17 is different for the top and bottom rows of images. Images on the top row are captured from a location behind the rover; the bottom row of images is captured from a location ahead of the rover.

After traversing a distance of about 10m from start, the rover stops, turns toward the goal, and re-analyzes the traversability of the terrain ahead of it. This time the front sector is found to have low traversability due to the large cluster of rocks located in this area. The left region is found to have low traversability due to the large sloped hill, and the right region is once again found to have high traversability. The rover thus turns to the right and proceeds into the safe region. At the point when the rover is within 1.5m of the goal, the weight on the traverse-terrain recommendation is reduced automatically, and the seek-goal behavior becomes dominant. At this point, the rover heads directly toward the goal and stops when it is reached.



FIGURE 11.17 Navigation path using strategic navigation behaviors. Top-left image shows the initial position; bottom-right image indicates goal achievement.

As shown in the sequence of test images, the navigation system directs the rover through the *safest* traversable regions. The combination of terrain assessment, safety, and strategic navigation modules in the safe navigation system thus demonstrates the viability of soft-computing algorithms for enabling safe traversal of the rover on challenging terrain.

11.7 SUMMARY AND CONCLUSIONS

Safe and autonomous long-range navigation of a rover on hazardous natural terrain offers significant technical challenges. An autonomous planetary rover must be able to operate intelligently with minimal interaction with mission operators on Earth. To accomplish this goal, the rover must have the on-board intelligence needed to traverse highly-unstructured, poorly-modeled terrain with a high level of robustness and reliability. For operation over extended time and distance, some capacity for built-in safe operation and health cognizance is required. The rover on-board software intelligence must be capable of supporting real-time navigation and motion planning based on poor and noisy sensor data. At the same time, it must be realizable in practical rover computing hardware. As such, efficient algorithms are essential for intelligent control.

As a goal, we have focused on achieving human driver performance through the application of soft computing techniques. This chapter presents the current state of development of a safe rover navigation system designed with this goal in mind. Various components of the safe navigation system are described in detail. Several soft computing solutions to different aspects of the rover navigation problem are also presented. Through this research and application experience, we have found that fuzzy logic provides a natural framework for expressing the human reasoning and decision-making processes for driving a rover on hazardous terrain. The human driving strategy can be transferred easily to the on-board rover navigation system and executed in real-time.

Robot navigation strategies based on fuzzy logic offer major advantages over analytical methods. First, the fuzzy rules that govern the robot motion are easily understandable, intuitive, and emulate the human driver's experience. Second, the tolerance of fuzzy logic to imprecision and uncertainties in sensory data is particularly appealing for outdoor navigation because of the inevitable inaccuracies in measuring and interpreting the terrain quality data, such as slope and roughness. And third, the fuzzy logic strategy has a modular structure that can be extended very easily to incorporate new capabilities -- whereas this requires complete reformulation for analytical methods. Multiple fuzzy behaviors can be blended readily into a unified navigation strategy that permits smooth interpolation between behaviors, thereby avoiding abrupt and discontinuous behavioral transitions.

The addition of the on-board terrain sensing and traversability analysis, coupled with the traverse-terrain behavior that takes advantage of this information, is a significant and novel contribution. These capabilities allow the navigation system to take preventive measures by "looking ahead" and preventing the rover from potential entrapment in rock clusters and other impassable regions and instead, guiding the vehicle to circumnavigate such regions. The technology described herein will lead to survivable rover systems that are of practical use for performing long-duration missions involving long-range traversal over challenging and high-risk terrain.

ACKNOWLEDGEMENT

The research described in this chapter was performed at the Jet Propulsion Laboratory, California Institute of Technology, under contract with the National Aeronautics and Space Administration.

REFERENCES

1. DeLong, B., *4-Wheel Freedom: The art of off-road driving*, Paladin Press, Boulder, CO, 1996.
2. Graydon, D. and Hanson, K. (Eds.). *Mountaineering: The freedom of the hills*, The Mountaineers, Seattle, WA, 1997.
3. Tunstel, E., Fuzzy-behavior synthesis, coordination, and evolution in an adaptive behavior hierarchy", chap. 9 in Saffiotti, A. and Driankov, D. (Eds.) *Fuzzy logic techniques for autonomous vehicle navigation*, Springer-Verlag Studies in Fuzziness and Soft Computing Series, Berlin/Heidelberg, 2000.
4. Morrison, J. C. and Nguyen, T. T., On-board software for the Mars Pathfinder microrover, *Proc. 2nd IAA Intl. Conf. on Low-Cost Planetary Missions*, 1996.
5. Washington, R. et al. Autonomous rovers for Mars exploration, *Proc. IEEE Aerospace Conf.*, 1999.

6. Huntsberger, T.L. and Rose, J., BISMARC: a biologically inspired system for map-based autonomous rover control, *IEEE Trans. on Neural Networks*, 11(7/8), 1497, 1998.
7. DeCoste, D., Adaptive resource profiling, *Proc. Intl. Symp. on AI, Robotics and Automation in Space*, Noordwijk, Netherlands, 1999.
8. Rosenblatt, J. K., DAMN: A distributed architecture for mobile navigation, *J. Experimental and Theoretical AI*, 9(2/3), 339, 1997.
9. Kelly A. and Stentz A., An approach to rough terrain autonomous mobility, *Proc. Intl. Conf. on Mobile Planetary Robots*, 1997.
10. Wilcox, B.H., Non-geometric hazard detection for a Mars microrover, *Proc. NASA/AIAA Conf. on Intelligent Robotics in Field, Factory, Service, and Space*, 675, 1994.
11. Arkin, R.C., Homeostatic control for a mobile robot: dynamic replanning in hazardous environments, *J. Robotic Syst.*, 9(2), 197, 1992.
12. Mauer, G. F., A fuzzy logic controller for an ABS braking system, *IEEE Trans. Fuzzy Syst.*, 3(4), 381, 1995.
13. Bauer, M. and Tomizuka, M. Fuzzy logic traction controllers and their effect on longitudinal vehicle platoon systems, California PATH Research Report, UCB-ITS-PRR-95-14, Univ. of California, Berkeley, 1995.
14. Palm, R. and Storjohann, K., Slip control and torque optimization using fuzzy logic, Chapter 12 in Jamshidi, et al. (Eds.) *Applications of fuzzy logic: towards high machine intelligent quotient systems*, 8, Prentice-Hall PTR, Upper Saddle River, NJ, 1997.
15. Colyer, R. E. and Economou, J. T., Soft modelling and fuzzy logic control of wheeled skid-steer electric vehicles with steering prioritisation, *J. Approx. Reasoning*, 22, 31, 1999.
16. Van der Burg, J. and Blazevic, P., Anti-lock braking and traction control concept for all-terrain robotic vehicles, *Proc. IEEE Intl. Conf. on Robotics and Automation*, 1400, 1997.
17. Sreenivasan, S. V. and Wilcox, B. H., Stability and traction control of an actively actuated micro-rover, *J. Robotic Syst.*, 11(6), 487, 1994.
18. Marra, M., Dunlay, R. T. and Mathis, D., Terrain classification using texture for the ALV, *Proc. Mobile Robots III*, SPIE 1007, 64, 1988.
19. Murphy, R. R. and Dawkins, D. K., Behavioral speed control based on tactical information, *Proc. IEEE Intl. Conf. on Intell. Robots and Syst.*, 1715, 1996.
20. Gennery, D. B., Traversability analysis and path planning for a planetary rover, *J. Autonomous Robots*, 6, 131, 1999.
21. Krotkov, E., et al. Field trials of a prototype Lunar rover under multi-sensor safeguarded teleoperation control, *Proc. American Nuclear Society 7th Topical Meeting on Robotics and Remote Syst.*, 1, 575, Augusta, 1997.
22. Langer, D., Rosenblatt, J. K. and Hebert, M. A behavior-based system for off-road navigation, *IEEE Trans. on Robotics and Automation*, 10(6), 776, 1994.
23. Shiller, Z. and Gwo, Y. R. Dynamic motion planning of autonomous vehicles, *IEEE Trans. on Robotics and Automation*, 7(2), 241, 1991.
24. Iagnemma, K., Genot, F. and Dubowsky, S. Rapid physics-based rough-terrain rover planning with sensor and control uncertainty, *Proc. IEEE Intl. Conf. on Robotics and Automation*, 3, 2286, Detroit, 1999.
25. Seraji, H., Traversability Index: A new concept for planetary rovers, *Proc. IEEE Intl. Conf. on Robotics and Automation*, 3, 2006, Detroit, 1999.
26. Seraji, H., Fuzzy Traversability Index: A new concept for terrain-based navigation, *J. Robotic Syst.*, 17(2), 75, 2000.
27. Horn, B., *Robot Vision*, MIT Press, MA, 1986.
28. Tsai, R. Y., A versatile camera calibration technique for high-accuracy 3D machine vision metrology using off-the-shelf TV cameras and lenses, *IEEE J. Robotics and Automation*, 3(4), 323, 1987.
29. Volpe, R. and Ivlev, R. A survey and experimental evaluation of proximity sensors for space robotics, *Proc. IEEE Intl. Conf. on Robotics and Automation*, 4, 3466, San Diego, 1994.
30. Everett, H. R., *Sensors for mobile robots: Theory and application*, A K Peters, Ltd., Wellesley, MA, 1995.